

Chapter IX

An Automated Approach to Historical and Social Explanation

NEUROCLASSIFICATION AS SOCIAL EXPLANATION

Since the beginning of the book, we know that solving archaeological problems implies answering a *double causality* question:

- Given the perception of visual inputs, the automated archaeologist should explain *what* social activity produced in the past the evidence perceived in the present.
- Once it knows what social activity was performed, where, and when, the automated archaeologist should explain *why* such activities were performed there and then, and in what way.

It is obvious that answering the first question is a condition to solve the second. In the same way as human archaeologists, the automated archaeologist needs to know what, where and when before explaining why some social group made something, and how. That is to say, only after having explained why archaeological observables are the way they are in terms of the consequence of some social activity or bio-geological process

performed in the past or in the present, the automated archaeologist will try to explain more abstract causal processes.

In previous chapters, we have been dealing, for the most part, with the first kind of problem. Automated discovery programs allow describing the action or process, which most probably caused the actual appearance of the archaeological record. Nevertheless, the automated archaeologist has not yet discovered *why* that activity took place there and then. Things become a bit more difficult when the automated archaeologist moves from the explanation of objects to the explanation of action and social behavior, because it should take into account people and people motivations.

The simplest way of understating social behavior is by classifying it. That means an automated archaeologist will explain people and social acts by recognizing them as members of some previously defined classes of people or events. Social explanation would then consist in the apprehension of the individual case as an instance of a general type, a type for which the intelligent machine should have a detailed and well-informed representation. Such a representation allows the

system to anticipate aspects of social activity so far unperceived.

It is usual in the social sciences to classify people according to social attributes. Computational intelligence tools can help in such a classification. In the social sciences, a neural network can classify a population into homogenous groups using factors such as age, sex, and other socio-economic variables to infer social status or position. A classical example is that of Meraviglia (1996, 2001) on social mobility, where input variables “gender,” “father’s education,” “father’s class position when age of respondent is 14,” and so on, are used to predict “son’s (or daughter’s) current class position.” Although this can be a good example of social explanation, no any social and historical explanation should be generated in that way. After all, we have already examined many examples of causal explanation based on alternative approaches, and we will present some other ways at the end of the chapter. In any case, we can explore the explanatory possibilities of “social classification” beyond trivial associations.

The most obvious way of classifying people to understand social dynamics in archaeology can be done in burial analysis. By studying the differences between graves according to the material remains of funerary rituals, an automated archaeologist can understand how social personality was built by a human group. Wealth and poverty, social elites and inequality, social marginality can be discovered by studying the quantity and diversity of grave goods, ways of body manipulation, etc. In general, the quantity of labor invested in a funerary ritual is a good estimation of the social importance of the buried individual.

Davino et al. (1999) have studied the Iron Age Italian cemetery of Sala Consilina. 173 graves were selected and described using as input variables the following nominal variables: preservation, burial length, sex/age, depth, quantity of grave goods, most frequent grave goods category (clay, metals), and type (according to the presence/absence

of weapons and other features). The goal was to calculate a classification rule for age/sex, based on grave attributes. A neural network was so created using 24 inputs (one for each qualitative value), three outputs (male, female, and child), and one hidden layer made of eight units. The network was trained with 110 graves whose skeletons were determined according sex and age, and used using the remaining 63. With training data, the network obtained 90.26 percent of correct classification, so it was used with the unclassified data, and was able to determine 39 male burials, 15 female, and nine children.

Although rather simple, this example is not trivial. It explains how we can explain the different social personality of women and men in Italian peninsula during 9th-7th centuries B.C. The limitations of the approach lie on the supervised nature of the neural network. The only “known” category to be predicted is “sex” or “age,” because there is an independent instrument for measuring them (physical anthropology analysis). If we could find additional known categories, a social classification approach would be very interesting for understanding social personality. For instance, if we estimate the quantity of labor invested in making some burials, we can build an input-output function relating the presence/absence of some funerary symbols and then predicting how they relate (in a nonlinear way) with social status, measured in terms of the quantity of labor invested in the burial. Additionally, we can use general information about a human group (productive mechanisms, degree of inequality, kinship, exchange, etc.) and build a neural network correlating observed material culture items (archaeological record) with interpreted social categories.

On the other hand, we can follow an unsupervised approach, that is to say, trying to build a general classificatory framework to explain observed differences. Let us consider the following simulated example. Suppose the automated archaeologist investigates a Late Bronze Age cemetery from Western Europe. 65 graves have

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